

# Assessment of Advanced Behaviours for Assistive Robotic Wheelchairs

Bojan Andonovski

Submitted in fulfilment of the requirement  
for the degree of Master of Science



The University of Technology, Sydney

The Faculty of Engineering and Information Technology

Mechatronics and Intelligent Systems Group

Centre for Autonomous Systems

[www.uts.edu.au](http://www.uts.edu.au)

Supervisor : Dr. Jaime Valls Miró

Co-Supervisor : Prof. Gamini Dissanayake

February 2016

# Declaration of Authorship

I, **Bojan Andonovski**, certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signed:

---

Date: 24/02/2016

---

# Acknowledgements

First and foremost, I would like to thank my thesis advisors, Dr. Jaime Valls Miró and Prof. Gamini Dissanayake, for offering me every opportunity to learn and grow as a researcher. Pursuing a Master wouldn't have been possible without their constant advice and support in all areas call from writing papers, doing research presentation, participating in different forums on world stage.

I would also like to thank all the bright minds who were around me at the Centre of Autonomous Systems (CAS), especially James Poon, for all the intelligent conversations, coffee breaks and “volunteering” for experiments, the results of which are collected in different chapters.

# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	Research Problem . . . . .	1
1.2	Motivation . . . . .	2
1.3	Research Objectives . . . . .	3
1.4	Approach and Methodology . . . . .	4
1.5	Thesis Overview . . . . .	6
1.6	Related Publications . . . . .	7
1.7	Ethical and Risk Consideration . . . . .	7
<b>2</b>	<b>A Sensor Package for PMDs Mapping and Tracking</b>	<b>8</b>
2.1	Introduction . . . . .	8
2.2	Related Work . . . . .	9
2.3	Sensor Package on the PMD Platform . . . . .	12
2.4	Mapping and Tracking . . . . .	14
2.4.1	Map Building . . . . .	15
2.4.2	Pose Estimation Approaches Background . . . . .	18
2.4.3	Comparing the Estimated Pose of Wheelchairs Platforms . . . . .	20
2.5	Summary . . . . .	26
<b>3</b>	<b>Automatic Analysis and Evaluation of PMDs Navigational Parameters</b>	<b>27</b>
3.1	Introduction . . . . .	27
3.2	Related Work . . . . .	28

3.3	Additional Navigational Parameters . . . . .	30
3.3.1	Alignment with Beds . . . . .	34
3.3.2	Minimum distance to Doors . . . . .	35
3.3.3	Velocity Profiles . . . . .	37
3.4	Experimental Evaluations of the Extracted Navigational Parameters . .	40
3.5	Summary . . . . .	46
<b>4</b>	<b>Machine Learning for Performance Classification</b>	<b>47</b>
4.1	Introduction . . . . .	47
4.2	Related Work . . . . .	47
4.3	Background in Machine Learning and Data Mining . . . . .	50
4.4	Extracting Parameters for an Assessment . . . . .	52
4.4.1	Experiment Setup and Data Collection . . . . .	53
4.4.2	Graphical User Interface . . . . .	56
4.4.3	Parameter Selection . . . . .	57
4.5	Classification Methodology . . . . .	60
4.5.1	Classification Results . . . . .	63
4.6	Summary . . . . .	67
<b>5</b>	<b>Conclusion and Future Work</b>	<b>68</b>
5.1	Conclusions . . . . .	68
5.2	Future Work . . . . .	69

# List of Tables

3.1	Yaw angle and distance to bed . . . . .	34
3.2	Minimum distance to the door . . . . .	36
3.3	Specific user performance metrics and OT scores during the “Advance task 3”. . . . .	42
3.4	Wheelchair speeds - linear (m/sec) and angular ( $^{\circ}$ /sec) - and OT scores over all tasks . . . . .	42
4.1	Task Datasets . . . . .	53
4.2	10m Task Parameter Statistics . . . . .	60
4.3	180deg Task Parameter Statistics . . . . .	60
4.4	Ramp Task Parameter Statistics . . . . .	60
4.5	Time-domain RF . . . . .	63
4.6	Time-domain Support Vector Machine . . . . .	63
4.7	Parametric RF . . . . .	63
4.8	Accuracies (%) . . . . .	65
4.9	Cohen’s Kappa . . . . .	65
4.10	Speed selection for combined tasks . . . . .	67
4.11	Accuracy and Cohen’s Kappa for speed selection classification . . . . .	67

# List of Figures

2.1	The SmartWheeler robot platform . . . . .	9
2.2	NOAH wheelchair system (commercially available wheelchair equipped with stereo-vision camera and laptop) . . . . .	10
2.3	Map of laboratory as a part of the “CanWheel”project created by the mapping component. . . . .	11
2.4	Laser map of the facility with examples of system prompts. . . . .	12
2.5	Example of narrow passage and waypoint sequence determination (blue curve) . . . . .	13
2.6	Sensor package prototype - detail. . . . .	13
2.7	Sensor enclosure mounted on PoW wheelchair . . . . .	14
2.8	UTS wheelchair platform with closeup of sensor package . . . . .	15
2.9	Map of the PoW indoor environment build by different methods. . . . .	16
2.10	Map of of the level 2 at UTS building build by diffeernt methods. . . . .	17
2.11	Gmapping Map of the GDS experiment environment . . . . .	18
2.12	Hector Mappings Map of the GDS experiment environment . . . . .	18
2.13	System overview of the AMCL solution. . . . .	19
2.14	Overview of the Hector Mapping SLAM system. . . . .	20
2.15	The extended Kalman filter approach fusing virtual odometry and IMU. . . . .	21
2.16	Estimated pose with AMCL and Hector Mapping by Run1 and User3. . . . .	21
2.17	Estimated pose with Robot Pose EKF by Run1 and User3. . . . .	22

2.18	Wheelchair trajectory while performing one of the task runs in PoW. Light grey is empty space (i.e. the room), dark grey is unknown (beyond the walls), green is the trajectory followed, white/green/red icons represent the orientation and edges of the wheelchair. Pylons used during the zig-zag motion are shown in red, while the right edge of the bed in the left room is shown in blue. . . . .	22
2.19	Trajectory while performing Task in CAS (Segway robot). . . . .	23
2.20	Hector Mapping pose and raw odometry (wheelchair run at level 2 UTS). . . . .	24
2.21	AMCL pose and raw odometry (wheelchair run at level 2 UTS). . . . .	24
2.22	Robot Pose EKF fusing virtual odometry and IMU (wheelchair run at level 2 UTS). . . . .	25
2.23	Robot Pose EKF fusing real odometry and IMU (wheelchair run at level 2 UTS). . . . .	25
2.24	Estimated position tracking in XY coordinates frame . . . . .	26
3.1	Travel along a sloped platform and align to a wall stations of the WST, with an intelligent wheelchair. . . . .	28
3.2	Move forward through a door and travel through increased rolling resistance stations of the WST, with an intelligent wheelchair. . . . .	29
3.3	Trajectories followed by the wheelchair platform during the 1 and 2 task runs. Light grey is empty space (i.e. the room), dark grey is unknown (beyond the walls), green is the trajectory followed, white/green/red icons represent the orientation and edges of the wheelchair. Pylons used during the zig-zag motion are shown in red, while the right edge of the bed in the left room is shown in blue. . . . .	32
3.4	Trajectories followed by the wheelchair platform during the 3 and 4 task runs. Light grey is empty space (i.e. the room), dark grey is unknown (beyond the walls), green is the trajectory followed, white/green/red icons represent the orientation and edges of the wheelchair. Pylons used during the zig-zag motion are shown in red, while the right edge of the bed in the left room is shown in blue. . . . .	33



3.5	Bed alignment component of the advanced task 3 by Users 1 and 2. . .	35
3.6	Bed alignment component of the advanced task 3 by Users 3 and 4. . .	36
3.7	Minimum distance to Doors with the visualization marker of the advanced task 3 by Users 1 and 2. . . . .	37
3.8	Minimum distance to Doors with the visualization marker of the advanced task 3 by Users 3 and 4. . . . .	38
3.9	Linear velocity profiles for Task 1 and 2 runs. . . . .	39
3.10	Linear velocity profiles for Task 3 and 4 runs. . . . .	40
3.11	Angular velocity profiles for Task 1 and 2 runs. . . . .	41
3.12	Angular velocity profiles for Task 3 and 4 runs. . . . .	43
3.13	Linear velocity profiles (segway robot). . . . .	44
3.14	Angular velocity profiles (segway robot). . . . .	44
3.15	Linear velocity profiles (UTS wheelchair platform). . . . .	45
3.16	Angular velocity profiles (UTS wheelchair platform). . . . .	46
4.1	Recorded data distribution for 10m runs. . . . .	52
4.2	Raw data signals of instances class 1. Linear velocity over time . . . . .	53
4.3	Raw data signals of instances class 1. Angular velocity over time . . . . .	54
4.4	Raw data signals of instances class 1. Orientation over time . . . . .	54
4.5	Raw data signals of instances class 4. Linear velocity over time . . . . .	55
4.6	Raw data signals of instances class 4. Angular velocity over time . . . . .	55
4.7	Raw data signals of instances class 4. Orientation over time . . . . .	56
4.8	Ramp and Turn Angle by ramp up and 180° turn tasks . . . . .	56
4.9	Trajectories followed by the wheelchair platform during the assessment task runs. . . . .	57
4.10	Test ramp (6° gradient) . . . . .	57
4.11	Assessment GUI. . . . .	58
4.12	Graphical representation of the linear and angular velocity and travelled distance for 10m forward task. . . . .	59
4.13	Results of the Parametric transformations . . . . .	61
4.14	Samples distribution . . . . .	62

4.15 Transformation of one instance from time domain using Autoregression	62
4.16 Summary of results for best classifier on 3 tasks . . . . .	64

# Abbreviations

2D	Two Dimensional
ADL	Activities of Daily Living
AMCL	Adaptive Monte Carlo Localisation
ARMA	AutoRregressive Moving-Average
AT	Assistive Technology (AT)
ATOM	Assistive Technology Outcome Measure
AR	AutoAegressie
BN	Bayesian Network
CAS	Centre of Autonomous Systems
DBN	Dynamic Bayesian Network
EKF	Extended Kalman Filter
EKG	Electrocardioraph
FIM	Functional Independence Measure
FEW-Q	Functional Evaluation in a Wheelchair Questionnaire
GUI	Graphical User Interface

HMM	Hidden Markov Model
IR	Infra Red
IPW	Intelligent Power Wheelchair
IMU	Inertial Measurement Unit
IWS	Intelligent Wheelchair System
KDD	Knowledge Discovery from Databases
KNN	K-Nearest Neighbors
MCL	Monte Carlo Localisation
MA	Moving-Average
MDP	Markov Decision Process Models
LPC	Linear Prediction Coding
OCAWUP	Obstacle Course Assessment of Wheelchair User Performance
OT	Occupational Therapist
OTFACT	Occupational Therapy Functional Assessment Compilation Tool
PCDA	Power-Mobility Community Driving Assessment
PIADs	Psychosocial Impact of Assistive Devices
PIDA	Power-Mobility Indoor Driving Assessment
PMD	Powered Mobility Devices
PoW	Prince of Wales Hospital
ROS	Robot OPERating System

POMDP	Partially Observable Markov Decision Process
PN	Probabilistic Networks
RF	Random Forest
SLAM	Simultaneous Localisation and Mapping
SVM	Support Vector Machine
UTS	University of Technology Sydney
WhOM	Wheelchair Outcome Measure
WST	Wheelchair Skills Test
WST-P	Wheelchair Skills Test Powered

# Abstract

*Research demonstrates that use of appropriate Assistive Technology (AT) is associated with increased independence and reduced need for ongoing care and support. Powered mobility devices (PMDs) such as power wheelchairs and scooters are proving to be useful pieces of assistive technology. This study focuses on developing and assessing the validity of a stand-alone sensor package and algorithms to help the assessment by an Occupational Therapists (OT) whether a person has the capacity to safely and efficiently operate a powered mobility device such as a wheelchair in their daily activities. This is accomplished by analysing data computed from a standalone sensor package fitted on a wheelchair platform. The proposed solution consists of a suite of sensors capable of inferring navigational features from the platform it is attached to (e.g. trajectories, map of surroundings, speeds, distance to doors, etc). The study aims to compare and contrast objective data derived from a PMD mounted sensor package with subjective data obtained using a standard Occupational Therapy assessment. The research work demonstrated that accurate, reliable objective data from a sensor package can be used to augment the Occupational Therapists subjective assessment. Furthermore, the task-specific parameters that may provide the most relevant user information for the assessment are automatically revealed through a machine learning approach. Machine learning automated assessment classification tests, with data attained from multiple runs of able clients simulating varying degrees of erraticness in their driving skills while they performed the assessment tasks, have indicated success rates in the order of 85%.*